Progress on Simulating function values and inferring B_a, B_b, B_c

Doesn't work yet. Last week, I directly simulated values of a_i, b_i, c_i for patient with covariate x_i, assuming no noise in the model ($\phi^a = \phi^b = \phi^c = 0$) and was able to infer B_a, B_b, B_c, as they were the linear coefficients in *independent* generalized linear models (independent given the data, which in that case was a_i, b_i, c_i).

However this week, the data is no longer a_i, b_i, c_i, but actual function values for a patient at particular times, $g_i^*(t; a_i, b_i, c_i)$. I fix B_a, B_b, B_c. Simulation is done with no noise - equivalent to setting $\phi^a = \phi^b = \phi^c = \phi^{noise} = 0$. Start with a cohort of patients - choose covariates for each patient. For each patient, I picked a few time points, and added function values at those times as data. Inference was a lot more difficult here, because now, B_a, B_b, B_c are correlated given the data, which is no longer the a_i, b_i, c_i.

Debugging approach

- Make $g_i(t; s_i, a_i, b_i, c_i)$ more simple. Tried:
  1. $g_i(t; s_i, a_i, b_i, c_i) = a_i$. Then, B_b and B_c are independent of the data and come from the prior. Don't have to worry about correlation of B_a with other parameters. This works.
  2. $g_i(t; s_i, a_i, b_i, c_i) = a_i + b_i * t$. B_c is independent of the data. Posterior for B_a and B_b are correlated, but inference still worked.
  3. $g_i(t; s_i, a_i, b_i, c_i) = s_i[(1 - a_i) - b_i(1 - a_i)(e^{-t})]$. This did not work. Plots to follow.
- Forcing noise parameters to be close to 0 by making $\lambda_a, \lambda_b, \lambda_c, \lambda_{noise}$ very high.
- Trying Metropolis Hastings vs Adaptive Metropolis Hastings didn't help in case 3.

Diagnostic plots for error case

Simulation was done using g_i as in item 3 above. Selected 1 dimensional covariate for 15 patients. Set $B_a = -1.0, B_b = 1.0, B_c = 1.0$. I start the MCMC from the MLE parameters.

- Figure 1: Set all parameters to maximum likelihood values. Then, vary B_a, B_b, B_c one at a time, holding other parameters fixed to see if likelihood surface is flat there.
- Figure 2: The simulated datapoints. The actual times I chose to 'measure' the function values at are denoted by the dots. Purpose was to see if changing the covariate x_i affected the corresponding curves.
- Figures 3 and 4: Trace of parameters that vary in the chain.
- Figure 5: Histogram of B_a, B_b, B_c.
- Figure 6: The curves of the patients, plotted using the mean posterior value for B_a, B_b, B_c. Purpose was to see whether, despite the coefficients being different, if the curves looked similar.

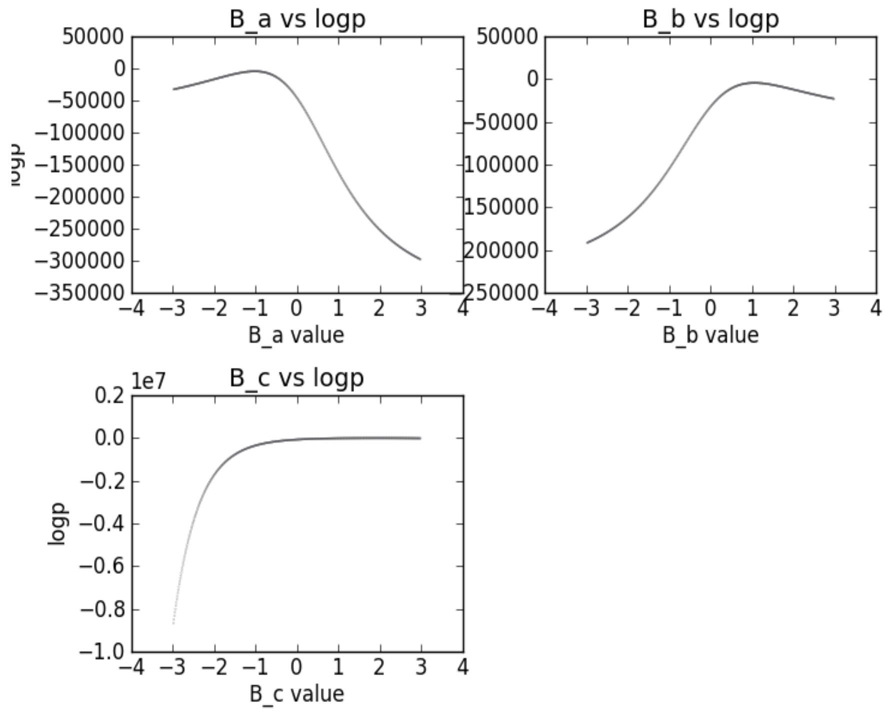

Figure 1: Likelihood surface vs B_a, B_b, B_c at MLE

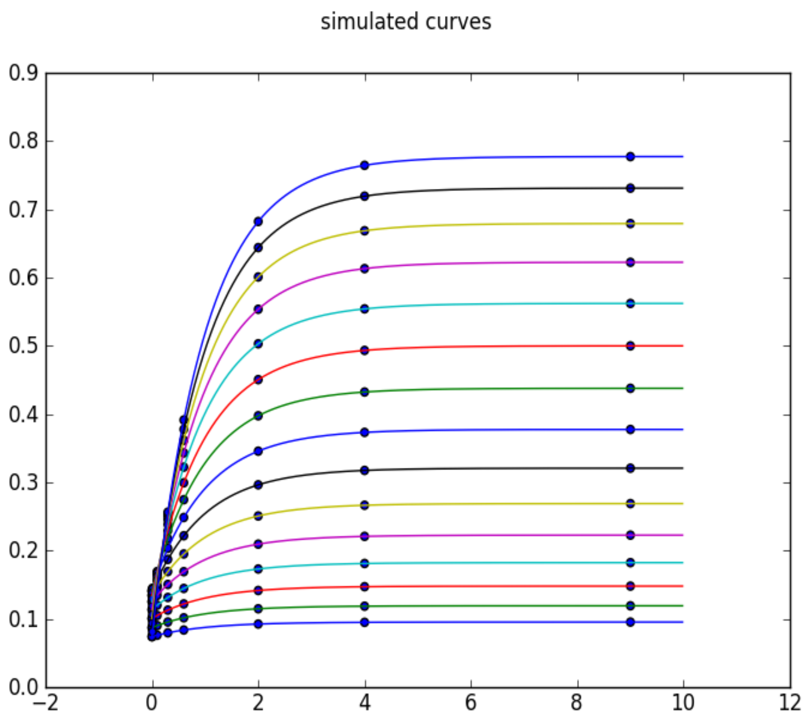

Figure 2: Simulated Curves of the Cohort

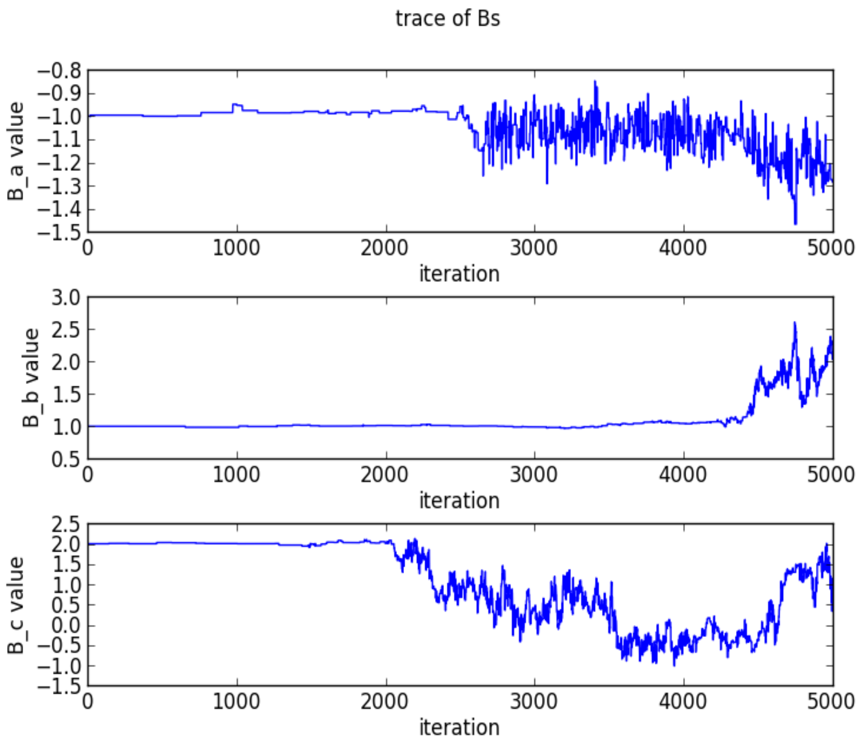

Figure 3: Trace of B_a, B_b, B_c

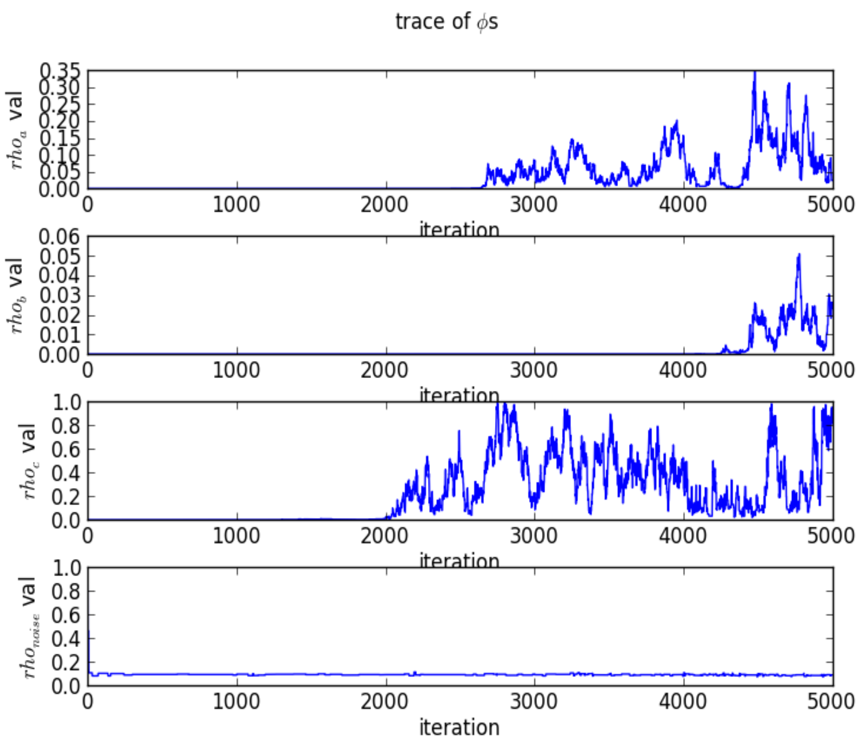

Figure 4: Trace of ϕ's

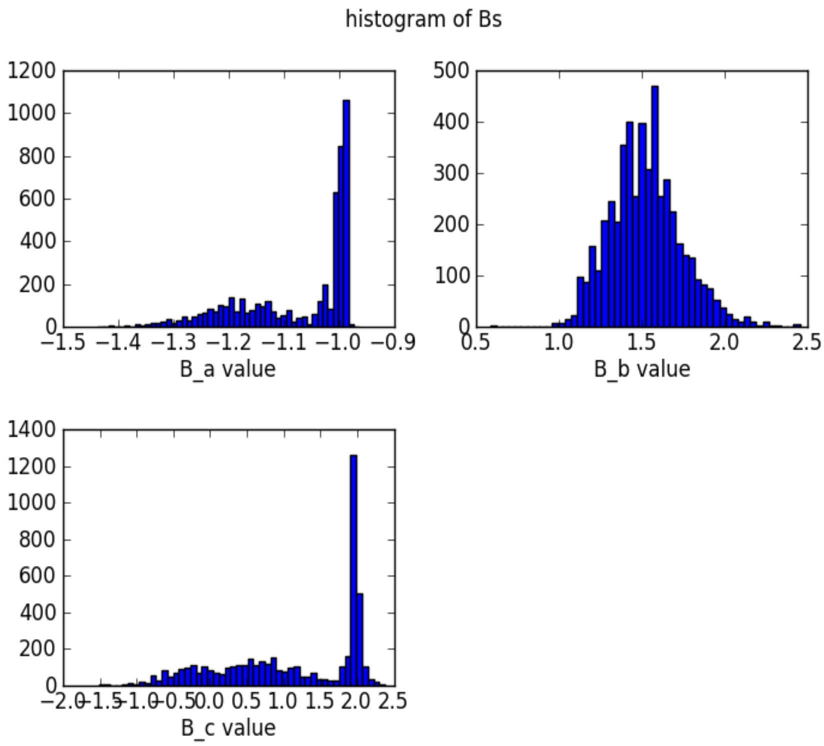

Figure 5: Histogram of B_a, B_b, B_c

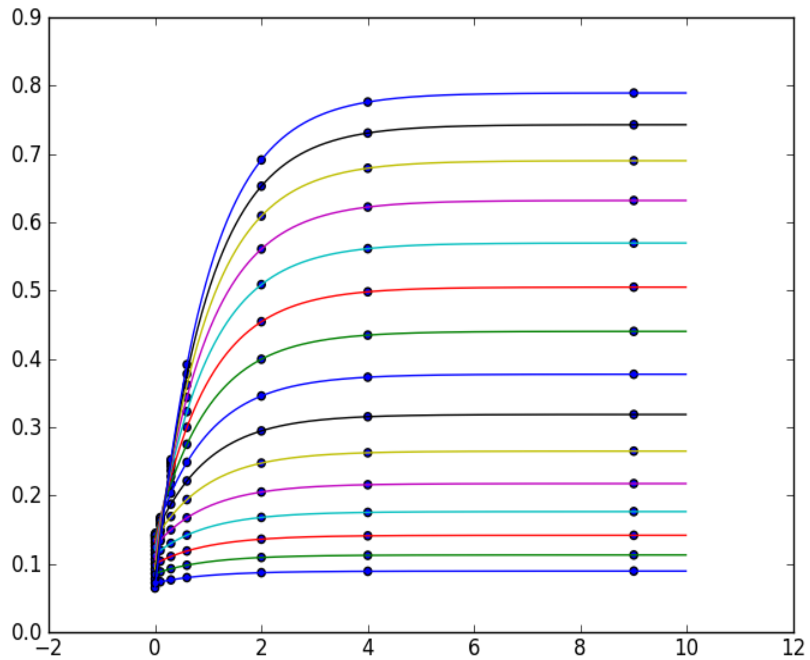

Figure 6: Posterior Curves of the Cohort